# Fuzzy clustering Approach in segmentation of T1-T2 brain MRI

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*Abstract* −**Segmentation is a difficult and challenging problem in the magnetic resonance images, and it considered as important in computer vision and artificial intelligence. Many researchers have applied various techniques however fuzzy c-means (FCM) based algorithms is more effective compared to other methods. In this paper, we present a novel FCM algorithm for weighted bias (also called intensity in-homogeneities) estimation and segmentation of MRI. Normally, the intensity inhomogeneities are attributed to imperfections in the radio-frequency coils or to the problems associated with the image acquisition. Our algorithm is formulated by modifying the objective function of the standard FCM and it has the advantage that it can be applied at an early stage in an automated data analysis. Further this paper proposes a center knowledge method in order to reduce the running time of proposed algorithm. The proposed method can deal with the intensity in-homogeneities and image noise effectively. We have compared our results with other reported methods. The results using real MRI data show that our method provides better results compared to standard FCM based algorithms and other modified FCM-based techniques.**

*Index Terms* − **Bias field, MRI, FCM, Segmentation, Data analysis.**

## I. INTRODUCTION

MRI segmentation techniques [13, 16] are an essential technique for assisting an image-based diagnosis. Manual segmentation is a difficult and time consuming task, which makes an automated breast cancer segmentation [23] method desirable. The automated segmentation [19] of MR images into anatomical tissues, fluids, and structures is an interesting field in medical image analysis. Automated segmentation methods based on artificial intelligence techniques were proposed in (Clark et al., [8]; Fletcher Heath et al., [12]). Gering et al. [14] proposed a method that detects deviations from normal brains using a multilayer Markov random field framework. In the last decades, fuzzy segmentation algorithms, especially the fuzzy c-means algorithm (FCM), have been broadly used in the image segmentation [24] and such a success mostly attributes to the introduction of fuzziness for the belongingness of each image pixel. Fuzzy c-means [4] allows for the ability to make the clustering methods able to retain more information from the original image

than the crisp or hard segmentation methods [20]. But segmentation [14] effectiveness is refusing by bias field, induced by radio frequency used during MRI exam [2, 7]. The bias field (intensity in-homogeneity) is induced by the radio- frequency coil in MRI and is a major problem in computer-based analysis of MRI data. A wide variety of algorithm has been developed for intensity non-uniformity correction (Lai and Fang et al. [18]). The homomorphic filtering approach to remove the multiplicative effect of in-homogeneity has also been commonly used due to its easy and efficient implementation (Johnston et al.[15]; Brinkmann et al. [6]). In addition these approaches assume that the intensity corruption effects are the same for different patients, which is not valid in general (Lai and Fang et al.[18] ). Dawant et al. [10] developed a two-step app roach for estimation of bias field. In this approach first ''reference points '' are selected for at least one tissue class (they used white matter) throughout the image, then a thin- plate spline is ''least-squared'' and fitted to the reference point data. They suggest the coefficient of variations as a measure for the degree of restoration. S.Shen et al. [22] presented a method is called improved fuzzy segmentation algorithm to correct the intensity non-uniformity during segmentation. Although MRI images may appear visually uniform, such in-homogeneities can cause serious misclassifications when intensity-based segmentation techniques are used (Ahmed et al. [2]). Another approach based on the fuzzy c -means (FCM) (Bezdek et al.[3]; Bezdek and James et al. [5]) clustering technique has been used for image segmentation [21]. In this paper, we present a modified fuzzy c -means (FCM) algorithm for intensity in-homogeneities estimation and segmentation of brain MR images. The bias field can deal with the intensity in-homogeneities and Gaussian noise effectively. It is based on the traditional fuzzy c- means (FCM) clustering algorithm and does not consider the effect of neighborhood attraction [1] to correct the intensity non – uniformity [9] during segmentation.

The paper is organized as follows. Section 2 presents the basics and proposed methods of this paper. Section 3, discusses the segmentation results and compares the results with other reported techniques. Section 4 concludes the paper.

## II. PROPOSED METHOD

### A. Fuzzy C-Means

Clustering methods can be considered as either hard (crisp) or fuzzy depending on whether a pattern data belongs exclusively to a single cluster or to several clusters with different degrees. Fuzzy c-means (FCM) [10] is an effective clustering algorithm for fuzzy clustering. Fuzzy C -means (FCM) clustering algorithm developed in the 1970s (Dunn [11]) and extended later (Bezdek [3], Bezdek et al [4]). The number of clusters is normally passed as an input parameter. The fuzzy c-means algorithm is based on minimization of the following objective function

$$J_{FCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} m_{ik}^{f} d_{ik}^{2} \tag{1}$$

where $c$ is the number of cluster centers or data subsets; n is the number of data points; $f$ is fuzzifier value (1 for hard clustering, and increasing for fuzzy clustering); $m_{ik}$ is the fuzzy membership value of pixel $k$ in cluster I; $d_{ik}^{2} = \|x_k - v_i\|^2$ is the Euclidean distance; $x_k$ is the $k$ th data points; $v_i$ is centriod of each cluster. $U$ is the fuzzy partition matrix and $V$ is the matrix of prototypes of clusters. The above FCM algorithm uses iterative operation to obtain U and V and finally minimizes the objective function.

### B Background

The observed MRI signal is modeled as a product of the true signal generated by the underlying anatomy, and a spatially varying factor called the gain field

$$Y_k = X_k N_k , \quad \forall k \in \{1, 2, ..., n\} \tag{2}$$

Where $X_k$ and $Y_k$ are the true and observed intensities at the $k$ th voxel, respectively and $N_k$ is the the gain field. The application of a logarithmic transformation to the intensities allows the artifact to be modeled as an additive bias field [19].

$$y_k = x_k + \omega_k \beta_k , \quad \forall k \in \{1, 2, ..., n\} \tag{3}$$

where $x_k$ and $y_k$ are the true and observed log-transformed intensities at the $k$ th voxel, respectively, $\omega_k$ is the weight at the $k$ th voxel and $\beta_k$ is the bias field at the $k$ th voxel. If the gain field is known, then it is relatively easy to estimate the tissue class by applying a conventional intensity-based segmenter to the corrected data.

### C Centre Knowledge Algorithm

**Step 1**: Let $X = \{x_1, x_2, ....., x_n\} \subset R^r$ be a data set, where r-Dimension. Find $s = \left\lfloor \dfrac{n}{c} \right\rfloor$ and $m_1, m_2, ....., m_n$, where $m_i = \sum x_{ij} \Big/ r$, i=1,2,…n, j=1,2,…, r, c be the number of cluster. Arrange $m_i$'s in ascending order.

**Step 2:** Rearrange the data matrix in respect of its relabelling mean value. (i.e) $X' = [x'_1, x'_2, \ldots x'_n]$. Partitioning the data into c groups. First group contains first $s$ data of X'. Second group contains second $s$ data of X'

$(c-1)^{th}$ group contains $(c-1)^{th}$ $s$ data of X'. $c^{th}$ group contains remaining all elements.

**Step 3:** Making a distance tables that show the distance between the elements within each group. (ie) If group k=$[x_1^k, x_2^k, \ldots x_n^k]$, the distance table is

| | $x_1^k$ | . . . ........... | $x_n^k$ |
|---|---|---|---|
| $x_1^k$ | $D_{11}^k$ | | $D_{1n}^k$ |
| . | . | ................. | . |
| $x_n^k$ | $D_{n1}^k$ | .................... | $D_{nn}^k$ |

**Step 4:** Select maximum distance from each distance table of groups. If $D_{ij}^k$ is maximum distance of $k$ th group , find the mean value $M_k$ of the elements $x_i$ and $x_j$. $k^{th}$ **cluster center** = $M_k$. k=1,2,…,c

### D Proposed Novel FCM [NFCM]

The new objective functions of FCM as shown below. Objective function

$$J_m = \sum_{i=1}^{c} \sum_{k=1}^{n} \mu_{ik}^{m} \left[ \alpha d_{ik}^2 + \delta \left( d_{ik}^* \right)^2 \right] + \frac{n}{c} \left( 1 - \sum_{i=1}^{c} \mu_{ik}^{m} \right) \tag{4}$$

where $d_{ik}^2 = \|x_k - v_i\|^2$ and $\left( d_{ik}^* \right)^2 = \|x_k + \varepsilon - b_k - v_i\|^2$, $\varepsilon \in (0,1)$ and $\alpha, \delta > 0$.

The objective function $J_m$ can be minimized in a fashion similar to the standard FCM algorithm. Taking the first derivatives o f $J_m$ with respect to $\mu_{ik}$, $v_i$ and $b_k$ and by setting them to zero results in three estimator of $U$, $V$, and $b$. With these estimators we

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can form an algorithm to compute the tissue class and bias field.

*a). Bias field estimation:* Taking the derivative of $J_m$ with respect to $b_k$ and setting the result to zero we

$$\left[ \sum_{i=1}^{c} \frac{\partial}{\partial b_k} \mu_{ik}^m \left( 2\delta \left( x_k + \varepsilon - b_k - v_i \right) (-1) \right) \right]_{b_k = b_k^*} = 0 \tag{5}$$

Differentiating the distance expression, we obtain:

$$\left[ \sum_{i=1}^{c} \frac{\partial}{\partial b_k} \mu_{ik}^m \left( 2\delta \left( x_k + \varepsilon - b_k - v_i \right) (-1) \right) \right]_{b_k = b_k^*} = 0 \tag{6}$$

The zero-gradient condition for the bias- field estimator is expressed as:

$$b_k^* = \left( (x_k + \varepsilon) - \frac{\sum_{i=1}^{c} \mu_{ik}^m v_i}{\sum_{i=1}^{c} \mu_{ik}^m} \right) \tag{7}$$

$\varepsilon \square (0,1)$ is the weight

*b). Cluster prototype updating:* Taking the derivative of $J_m$ with respect to $v_i$ and setting the result to zero, we have

$$v_i^* = \frac{\sum_{k=1}^{n} \mu_{ik}^m \left( (\alpha + \delta) x_k + \delta (\varepsilon - b_k) \right)}{\sum_{k=1}^{n} \mu_{ik}^m (\alpha + \delta)} \tag{8}$$

*c). Membership evaluation:* We compute this using Lagrange multiplier as shown below

$$L_m = \sum_{i=1}^{c} \sum_{k=1}^{n} \mu_{ik}^m \left[ \alpha d_{ik}^2 + \delta \left( d_{ik}^* \right)^2 \right] + \frac{n}{c} \left( 1 - \sum_{i=1}^{c} \mu_{ik}^m \right) + \lambda \left( 1 - \sum_{i=1}^{c} \mu_{ik} \right) \tag{9}$$

Taking the derivative of $L_m$ with respect to $\mu_{ik}$ and setting the result to zero, we have:

$$\mu_{ik}^* = \left( \frac{\lambda}{m} \right)^{\frac{1}{m-1}} \frac{1}{\left[ \alpha d_{ik}^2 + \delta \left( d_{ik}^* \right)^2 - \frac{n}{c} \right]^{\frac{1}{m-1}}} \tag{10}$$

Since we have:

$$\sum_{j=1}^{c} \mu_{ik} = 1$$

$$\mu_{ik}^* = \sum_{j=1}^{c} \left[ \left( \frac{\left( \alpha d_{ik}^2 + \delta \left( d_{ik}^* \right)^2 \right) - \frac{n}{c}}{\left( \alpha d_{jk}^2 + \delta \left( d_{jk}^* \right)^2 \right) - \frac{n}{c}} \right)^{\frac{1}{m-1}} \right]^{-1} \tag{11}$$

where $c$ is the number of clusters, $m = 2$.

### III. RESULTS AND DISCUSSION

In this work, we present proposed modified fuzzy clustering method for the segmentation of T1- T2- weighted brain MRI of the same patient. The brain T1-T2 weighted images corrupted by "Gaussian" noise for the purpose of experimental work (given in Fig. 1(a-b). In nature, the MRI images typically do not suffer from "Gaussian" noise, and we add such type of noise just for the comparison of robustness to noises of proposed algorithm. In this section, we describe some experimental results to compare the segmentation performance of the following algorithms, i.e. Improved fuzzy segmentation algorithm [IFS][16], KFCM[6], and proposed Novel FCM. We test these three methods on brain MR image. Figs. 2-4(a-b) show the segmentation results of IFS, KFCM, and NFCM respectively. As shown in Figs. 3-4(a-b), neither IFS nor KFCM can separate the six classes, while NFCM_S completely succeed in correcting and classifying the data as shown in Fig. 4a-b. From the images, we can see that both IFS and KFCM are affected by the noise badly, while NFCM nearly completely eliminate the effect of noise.
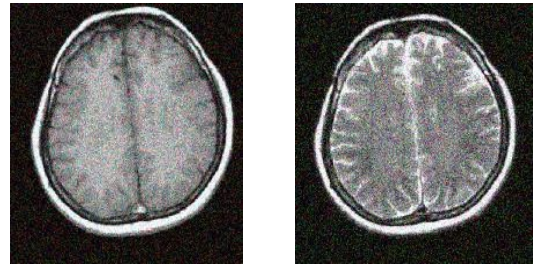


Fig. 1. (a) T1 corrupted by Gaussian noise, (b) T2 corrupted by Gaussian noise
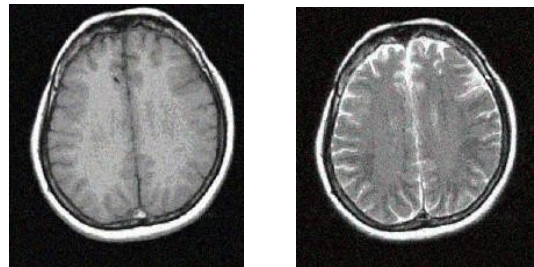


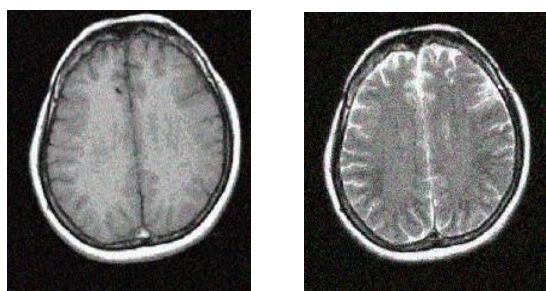Fig. 2. (a) T1 Segmented by IFS, (b) T2 Segmented by IFS

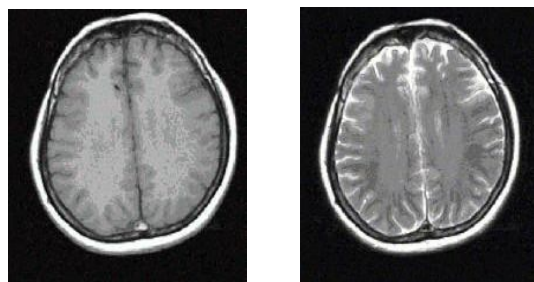Fig. 3. (a) T1 Segmented by KFCM, (b) T2 Segmented by KFCM



Fig. 4. (a) T1 Segmented by NFCM, (b) T2 Segmented by NFCM

Table I. Segmentation Accuracies

| No. of Clusters | Silhouette Value | Accuracy |
|---|---|---|
| IFS | 0.45 | 45% |
| KFCM | 0.51 | 51% |
| Proposed NFCM | 0.73 | 73% |

Table I gives the segmentation accuracy of the three algorithms on two different T1-T2 noisy images, where segmentation accuracy is defined using silhouette value in (Kannan S. R. [17]). These silhouette average values measures the degree of confidence in the clustering assignment of a particular observation, with well-clustered observations having values near 1 and poorly clustered observations having values near -1. From Table I, the best clustering validity 78 % was obtained for proposed method during the experimental work on brain image data. Further, it is clear from Fig. 4(a-b) that our proposed method completely succeeded in correcting and classifying the breast data and almost it eliminated completely the effect of noise in images. The other two IFS and KFCM techniques partially corrected the misclassified pixels given in Figs. 2-3(a-b). As can be seen, the clustering results of our Modified Fuzzy C-Means clustering algorithms were superior to those obtained by using other two algorithms which we proposed.

## IV. CONCLUSION

This paper presents a new novel fuzzy clustering algorithm with canter knowledge method for segmentation of brain T1 and T2 weighted images. This paper described experimental results on real MR images which corrupted with Gaussian noise to show the segmentation performance of proposed method. The segmentation results of proposed method have compared by existing methods. Further, the segmentation accuracy was obtained using Silhouette method and the proposed algorithm produces high segmentation accuracy than existed methods. The results reported in this paper show that the proposed novel objective function of fuzzy c-means is an effective approach to construct a robust image segmentation algorithm.

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